

Todd S. Rosenstock · Andreea Nowak
Evan Girvetz *Editors*

The Climate-Smart Agriculture Papers

Investigating the Business
of a Productive, Resilient and
Low Emission Future



Springer Open

Chapter 15

Household Welfare Effects of Stress-Tolerant Varieties in Northern Uganda



Chris M. Mwungu, Caroline Mwongera, Kelvin M. Shikuku, Mariola Acosta, Edidah L. Ampaire, Leigh Ann Winowiecki, and Peter Läderach

15.1 Introduction

In most developing countries agriculture plays a significant role in enhancing food security among smallholder farmers. It is regarded as a significant economic activity that can reduce absolute and relative poverty among smallholder farmers in Sub-Saharan Africa (SSA) (Odame et al. 2013). However, both presently and in the future, the agricultural sector is increasingly threatened by the adverse impacts of climate risks. As a result of climate change, inconsistent and unstable agricultural yields will ultimately increase the risk of food and nutritional insecurity among the vulnerable populations in SSA. It is expected that climate change will ultimately lead to increased nutritional disorders, diseases, hunger and socio-economic instability in Africa (Msowoya et al. 2016). Since most families in rural SSA provide own farm labour in agriculture (Dieterich et al. 2016), poorly fed families may provide low quality labour, which can also affect production. With continuous deterioration in production over seasons, the standards of living for farmers in rural Africa will be compromised. In the case of Uganda, a decrease of a 2–4% in Gross Domestic Product is foreseen, if sufficient measures to combat climate change are not taken into consideration (Markandya et al. 2015).

C. M. Mwungu (✉) · C. Mwongera · K. M. Shikuku
International Centre for Tropical Agriculture (CIAT), Africa Regional Office, Nairobi, Kenya
e-mail: c.mwungu@cgiar.org

M. Acosta · E. L. Ampaire
International Institute of Tropical Agriculture (IITA), Kampala, Uganda

L. A. Winowiecki
World Agroforestry Centre (ICRAF), Nairobi, Kenya

P. Läderach
International Center for Tropical Agriculture (CIAT), Asia Regional Office c/o Agricultural Genetics Institute, Hanoi, Vietnam

Climate-smart agriculture (CSA) technologies, such as stress-tolerant varieties have the potential to increase productivity and reduce poverty levels of smallholder farmers (Food and Agriculture Organization (FAO) 2013). In addition, stress-tolerant varieties may reduce the risk of pests and diseases that are accelerated by climate change (Jellis 2009; Nyasimi et al. 2017). Among the challenges experienced by farmers in northern Uganda are a high prevalence of crop diseases and an increasing occurrence of inter- and intra-seasonal dry spells (Mwongera et al. 2014). Therefore, stress-tolerant varieties can reduce the cost of production and lower the economic risk of investing in agriculture. Although trade-offs are possible, adoption of stress-tolerant varieties can contribute to the three pillars of CSA by increasing production and enhancing the resilience of farming systems (Shiferaw et al. 2014). Furthermore, stress-tolerant varieties enhance the optimal use of available household resources and are, therefore, central to sustainable economic development (Khatri–Chhetri et al. 2017).

We carried out studies in 2015 to prioritise context-specific CSA practices for Nwoya District (Shikuku et al. 2015). The use of improved stress-tolerant varieties was ranked highest among the shortlisted CSA practices by stakeholders. However, the adoption of the stress-tolerant varieties was still low in the District, partly due to past experience of other improved varieties as well as a lack of financial resources. The most prevalent challenges to agriculture production, linked to climate stresses, were: the high prevalence of pests and diseases, unpredictable rainfall patterns, soil erosion, droughts and floods. Other practices that were selected as relevant to address these matters included: maize legume intercrop, agroforestry, silvo-pastoral systems and crop rotation. Few studies have assessed the impacts of climate change and climate-smart agriculture options on farm income, labour demand, food security and nutrition, thus empirical evidence is still insufficient. Existing studies include, Makate et al. (2016), which reported that households became more food secure and resilient to climate change on the adoption of crop diversification. Also, Manda et al. (2016), which argued that the adoption of improved varieties only increases the cost of production; but, when blended with a maize–legume intercrop, household crop income increased. And Brüssow et al. (2017), which found that the adoption of CSA technologies by farmers in Tanzania increased household food security in terms of diversity and stability. In this study, we assess the welfare effects of adopting stress-tolerant varieties in Nwoya District, using per capita crop income as a proxy to measure farmers' welfare. The study considered stress-tolerant varieties of maize, beans, cassava and groundnuts. To fill important gaps in the evidence, this study asked the following research questions: (i) what are the drivers for adoption of stress-tolerant varieties? (ii) What is the impact of adopting stress-tolerant varieties on households' welfare?

15.2 Data and Methods

The study used a household survey data set collected in Nwoya District, Uganda in October 2014. The District covers a geographical area of 4736.2 square kilometres (km²) and has an average population density of 36.99/km². Over the course of the

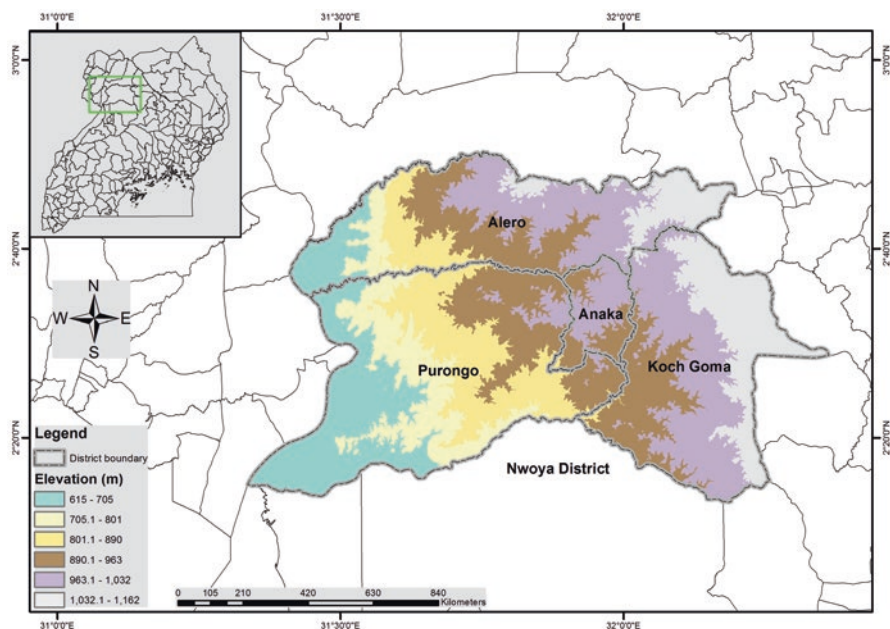


Fig. 15.1 Map of the study area—Nwoya District in Northern Uganda

year, the temperature varies from 18 to 36 °C. The region has a wet season that begins in March and ends in November each year. Planting of annual crops normally begins in April, while harvesting starts in July depending on the crop. Figure 15.1 presents a map of the study area. A detailed description of the study area, sample size, target population, sampling procedure and accessibility of the data is provided by Mwungu et al. (2017). Data were collected from 585 farm households in Nwoya District via one-to-one interviews. The survey questionnaire captured information on socio-demographics, dwelling characteristics, assets ownership, food availability, access to financial services, adoption of CSA technologies and practices, membership of agricultural groups, sources of agricultural information, farming activities and production for different crops at plot level, personal values, and farmers' perceptions of climatic changes. Empirical analysis began by assessing the determinants of adopting stress tolerant varieties using a binary choice logistic regression model. This analysis constituted the first step in the propensity score matching (PSM) technique of impact assessments. Within a regression framework, a binary choice model is specified as:

$$W_{it}^* = \beta x_i + \varepsilon_i$$

$$W_{it} = \begin{cases} 1, & \text{if } W_{it}^* > 0 \\ 0, & \text{otherwise} \end{cases} \quad (15.1)$$

where W_{it}^* is a latent unobserved variable whose counterpart, W_{it} , is observed in dichotomous form only; where $W_{it} = 1$ represents households that adopted a CSA

technology and $W_{it} = 0$ represents households that did not adopt; β refers to a vector of coefficients estimated by the model. The signs and magnitude of the marginal effects are important in explaining the effect of the independent variables on the adoption of improved varieties or simply the propensity to adopt. A vector of independent variables is represented by x while ε is the error term. The choice of the independent variables was informed by literature on the adoption of agricultural innovations (see, for example, Manda et al. 2016). This first step generated propensity scores, that is, the estimated probabilities of households to adopt stress tolerant varieties based on the observed covariates, x .

In the second step, average treatment effects (ATE) were estimated based on a matched sample of adopters and non-adopters, which was obtained using the propensity scores generated in the first step. Using this approach, we controlled for unobserved heterogeneity due to self-selection into adopter and non-adopter groups. The probability of self-selection bias in non-experimental studies might imply that the adopters are systematically different from non-adopters and, if this is not adequately controlled for, the estimated impacts may be biased and the conclusion misleading. The fundamental assumption in PSM is that outcomes are independent of treatment assignment and conditioned on explanatory variables. Furthermore, it is assumed that there is sufficient overlap in propensity scores so that both adopters and non-adopters have an equal probability greater than zero and less than one of adopting improved varieties. These two underlying assumptions are, respectively, referred to as the ‘conditional independence assumption’ and the ‘common support assumption’. Causal effect, therefore, refers to the difference between the observed and counterfactual household welfare. Following Becker and Caliendo (2007), average treatment on the treated (ATT) can be calculated by:

$$ATT = E(y_{1i}(1)|T=1) - E(y_{0i}(0)|T=0) \quad (15.2)$$

where ATT is the observed per capita net crop income for improved varieties adopters, y_{1i} is the observed average household welfare for adopters of improved varieties, while y_{0i} is the estimated household welfare if the adopters had not adopted improved varieties.

15.2.1 Description of Variables

Table 15.1 provides a detailed description of the variables used in the study. The choice of the variables used in this study was informed by literature from past studies on the adoption and impact of agricultural technologies (Bonabana-Wabbi 2002; Joshua Udoh and Titus Omonona 2008; Simtowe et al. 2012; Asayehegn et al. 2017).

Table 15.1 Measurement and description of variables

Variable description	Measurement
Outcome variable	
Per capita net crop income (USD)	Net crop income divided by household size
Household characteristics variables	
Household size (count)	Number of persons in the household
Sex of the household head (0/1)	Sex of the principal decision-maker in the household
Age of the household head (years)	Age of the principal decision-maker
Literacy index (index)	Ratio between household members with post-primary education and household size
Number of years residence in the village (years)	Number of years a farmer has lived in the village
Household wealth characteristics	
Asset index (index)	Index of number and type of assets owned to determine the well-being of the household
Institutional and access related variables	
Access to government extension (0/1)	Dummy for access to government extension officers
Access to farmer organisation (0/1)	Dummy for access to farmer organisation
Access to NGO information (0/1)	Dummy for access to NGO information
Access to demo plots (0/1)	Dummy for access to demo plots information
Access to credit services (0/1)	Access to credit services
Member of an agricultural group (0/1)	Membership of an agricultural group
Gender roles and personal values	
Training on personal values (0/1)	Training on personal values
Perceptions of climate change and associated risks	
Noticed change in climate (0/1)	Noticed a change in climate
Perceiving likely change in climate change in future (0/1)	Perception that climate will change in future
Perceiving reduced current rainfall (0/1)	Perception that rainfall amount received has reduced
Climatic shocks	
Experienced floods (0/1)	Experienced floods
Experienced drought (0/1)	Experienced drought
Food security variable	
Number of hunger months in a year (count)	Number of hunger months in a year

15.3 Results of Econometric Analysis

15.3.1 Determinants for Adoption of Improved Varieties

The logistic model was initially fitted in the first stage of the PSM to assess the factors that influence adoption of improved varieties and determine the propensity to adopt for each household. The dependent variable was a binary stress tolerant

varieties adoption. To establish the reliability of the estimates from the logit model, a variance inflation factor (VIF) test for multicollinearity and Hosmer–Lemeshow (HL) test for goodness of fit were conducted. The VIF test ruled out serious multicollinearity and the HL test showed that the logit model was properly specified. Additionally, the log likelihood ratio obtained was -608.5264 , which was statistically significant at 1%, while the pseudo- R^2 value of the model was 0.1421. This indicated overall significance of the logistic model and a good fit for the data. As shown in Table 15.2, the decision to adopt stress tolerant varieties was positively influenced by household size, gender of the household head, access to agricultural information from NGOs, perception of future changes in climate, number of years' residence in the village and the asset index. This indicated that for every unit increase in any of the variables, the probability of adopting improved varieties increases by the corresponding marginal effects.

These results are in harmony with other past studies on theoretical and empirical literature about agricultural technology adoption. For instance, farmers who had access to NGO information were 10.33% more likely to adopt stress-tolerant varieties than their counterparts. This is partly because access to information reduces uncertainty about new technologies as farmers become aware of the new technology and how to use it effectively. These findings are in agreement with (Bonabana-Wabbi 2002) which reported that farmers who had access to agricultural information had a higher probability of adopting integrated pest management technologies in Uganda. However, against our expectation, farmers who had access to demo plots information were not more likely to adopt improved varieties. We hypothesise the reason for this finding is based on the context of the study site. Communities in northern Uganda suffered conflict and were displaced in camps and have only resettled back in their farms within the last decade. Approaches relying on trust and social networks are, therefore, more likely to influence learning and the adoption of stress tolerant varieties. In this case, we see that learning through NGOs—most of which have been in the community for long periods and have built good relationships with the farmers—is likely to be more effective compared to demonstration plots, which are often set up for short periods. In addition, CSA technologies are context-specific and so might be the approaches used to promote CSA. In Nwoya District, for example, households as well as villages tend to be geographically quite far from each other. In such cases, farmers (in a previous and related study) indicate that distance to the plot was the main reason why they were not actively participating in the demonstration plots (Shikuku et al. 2015). Such farmers often demanded the reimbursement of transport and refreshments costs during training, without which they were unwilling to actively learn.

Household size had a positive effect on the adoption of stress tolerant varieties. This is plausible because a greater number of household members means there are more people available to provide the intensive labour that comes with the adoption of new technologies. This is in agreement with Adepoju and Obayelu (2013) who reported that household size was an important factor in determining the type of livelihood strategies adopted. The significance of the

Table 15.2 Determinants of adoption of improved varieties

Variable	ME	SE	<i>p</i> -value
Household characteristics variables			
Household size (count)	0.0130 ^a	0.0055	0.018
Sex of the household head (0/1)	−0.1248	0.0058	0.332
Natural log of age of the household head (years)	0.0449	0.0450	0.366
Literacy index (index)	0.1131	0.0908	0.213
Natural log of number of years in the village (years)	0.6283 ^a	0.0300	0.041
Household wealth characteristics			
Asset index (index)	0.1955 ^a	0.5058	0.018
Institutional and access related variables			
Access to government extension (0/1)	0.0642	0.0331	0.053
Access to farmer organisation (0/1)	−0.0532	0.0304	0.080
Access to NGO information (0/1)	0.1032 ^b	0.0326	0.002
Access to demonstration plots information (0/1)	−0.1402 ^b	0.0406	0.001
Access to credit (0/1)	−0.0556	0.0305	0.068
Member of an agricultural group (0/1)	0.0620	0.0493	0.209
Gender roles and personal values			
Training on personal values (0/1)	0.0186	0.0289	0.522
Perceptions of climate change and associated risks			
Noticed change in climate change (0/1)	−0.0809	0.0895	0.366
Perceiving likely change in climate change in future (0/1)	0.0931 ^b	0.0280	0.001
Perceived reduced current rainfall (0/1)	0.0324	0.0289	0.262
Climatic shocks			
Experienced floods (0/1)	0.0515	0.0301	0.088
Experienced drought (0/1)	0.0143	0.0321	0.656
Food security variable			
Number of hunger months (count)	−0.0107	0.0154	0.485
Sub-county fixed effects			
Alero	0.2840 ^b	0.0390	0.000
Anaka	0.0668	0.6209	0.282
Koch Goma	0.4524 ^b	0.0382	0.000
Purongo	—	—	—
Constant	−2.8014 ^b	0.7342	0.000
Log likelihood	−608.5264		
LR chi2 (22)	201.55		
Prob>chi2	0.000		
Pseudo-R ²	0.1421		

ME (marginal effects), *SE* standard error, *p*-value probability value

^aSignificance at 5%

^bSignificance at 1%

number of years of residence in the village meant that a farmer who stayed in the village for more than 1 year was 7.19% more likely to adopt new seed varieties. This could be attributed to strong social networks along with a greater number of years' farming experience in the village. Simtowe et al. (2012) also reported that farmers who'd lived in their village for a longer time were more likely to be exposed to the availability of improved pigeon pea varieties, unlike their counterparts, because of the social capital in information sharing. Asset index was used as a proxy for estimating the wealth of the farmers. Farmers with more assets are likely to have more money, equipment and materials that will aid easy access to new technologies. The results in Table 15.2 show that a 1% increase in the asset index increases the probability of adopting new varieties by 19.55%. This is in line with Tesfaye et al. (2016), where the authors reported that asset ownership was positively correlated with the adoption of improved wheat varieties in rural Ethiopia. Lastly, the significance of the variable 'noticed change in climate change' indicates that farmers who had noticed change were 10.98% more likely to adopt improved varieties. We can argue that such farmers know about the negative impacts of climate change and would, therefore, prefer to adopt technologies that will increase production and make them food secure, unlike their counterparts. Asayehegn et al. (2017) similarly argue that farmers who were aware of climate change were more willing to implement climate adaptation measures to mitigate themselves from the dangers.

15.3.2 Estimating the Impact of Improved Varieties Adoption Decision

In the second step of PSM, we applied three different matching algorithms: nearest neighbour matching, kernel matching, and radius matching. The PSM model was used to determine the impact of the different CSA technologies on household welfare. After matching, ATE was computed. The propensity scores for both adopters and non-adopters ranged from 0 to 1. The reduced magnitude of Pseudo- R^2 as well as the statistical insignificance of the p -values associated with the likelihood test, justified the choice of PSM model for our data. In addition, as shown in Table 15.3, there was a substantial reduction in bias after matching which is important in examining balancing powers of estimation. The reduction in the value and the insignificance of Pseudo- R^2 after matching indicated that there were no significant differences in the values of the independent variables for the adopters and non-adopters of stress-tolerant varieties after matching. Likewise, the p -values of the likelihood ratio test were insignificant after matching. Lastly, the mean and median bias were all below 20% justifying the choice of PSM model in this study.

Table 15.3 Statistical tests to justify matching

Matching method	Pseudo-R ²	Likelihood ratio Chi ²	p>Chi ²	Mean bias	Median bias
Before matching	0.1421	168.75	0.000	28.0	24.0
Radius matching	0.002	2.54	1.000	2.2	1.4
Kernel Based matching	0.014	17.16	0.309	5.9	6.4
Nearest neighbour matching	0.003	3.32	0.999	2.6	2.4

Table 15.4 ATT for household welfare

Matching algorithm	Treated (ATT)	Controls (ATT)	Difference	SE	t-stat	ATE
RM	1102.87	753.15	349.72	097.23	3.60	358.41
KBM	1102.87	808.89	293.98	122.94	2.39	319.77
NNM	1102.87	899.04	203.83	110.27	1.85	258.04

Note: The amount is stated in USD

RM radius matching, *KM* kernel based matching, *NNM* nearest neighbour matching, *SE* standard error, *t-stat* t-statistics

The estimates of the average adoption effects from all the three matching algorithms are presented in Table 15.4. The results showed that the adoption of stress tolerant varieties has a positive impact on household welfare. Results from all the three matching algorithms were consistent. As shown in Table 15.4, per capita crop income was higher for the adopters than the matched non-adopters. From the findings—assuming that the two groups were matched on the equality of their propensity score—we can infer that the difference in the household per capita income results from adopting stress tolerant varieties.

15.3.3 Sensitivity Tests for Estimated Average Treatment Effects

Statistically, it is important to test the reliability of the estimated values of ATT and ATE (Becker and Caliendo 2007). This helps the researcher to examine the sensitivity of the estimated treatment effect to small deviations in the propensity scores. Doing so also acts as a check on the quality of the comparison group. Due to the limitations of observed data, such as bias creation, sensitivity analysis helps in checking if the unobserved variation has a significant effect on the estimated values of ATT and ATE. As shown in Table 15.5, the significance level is unaffected even if gamma values are increased by threefold. This clearly shows that the estimated values of ATT and ATE will not change to any external deviation.

Table 15.5 Sensitivity analysis with Rosenbaum bounds

Gamma	sig+	sig–
1	0.093194	0.093194
1.25	0.757402	0.000394
1.5	0.990693	2.20E-07
1.75	0.999918	3.70E-11
2	1	2.80E-15
2.25	1	0
2.5	1	0
2.75	1	0
3	1	0

15.4 Implications for Development

This study assessed the drivers behind the adoption of stress-tolerant varieties and their impact on farmers' welfare. The results showed that household size, access to agricultural information from NGOs, perception of future changes in climate, number of years' resident in the village and asset index all have a positive influence on the propensity to adopt stress-tolerant varieties. Further results show that stress-tolerant varieties have the potential of increasing net crop income within a range of USD 500–864 per hectare per year, corresponding to an 18–32% increase. Our empirical results suggest the need to implement a bundled solution in scaling up the adoption of stress-tolerant varieties. Specifically, a bundled solution that includes the strengthened capacity of households to own farm assets and increased access to agricultural and weather information (relying on pathways reinforced by trust and social networks) can be effective for adaptation to climatic risks in northern Uganda. The findings support the view that, in a similar way, CSA interventions are context-specific as are the pathways for scaling up the adoption of these interventions. Overall, in harmony with existing literature, the adoption of stress-tolerant varieties as CSA technologies can be a corridor to improving the welfare of farm households in northern Uganda.

Acknowledgements This work was carried out by the International Center for Tropical Agriculture as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security. The project, Increasing Food Security and Farming System Resilience in East Africa through Wide-Scale Adoption of Climate-Smart Agricultural Practices, is funded with support from the International Fund for Agriculture Development.

References

- Adepoju AO, Obayelu OA (2013) Livelihood diversification and welfare of rural households in Ondo State, Nigeria *J Dev Agricult Econ* 5(12):482–489
- Asayehegn GK, Temple L, Sanchez B et al (2017) Perception of climate change and farm level adaptation choices in central Kenya. *Cahiers Agricult* 26(2):1–11

- Becker SO, Caliendo M (2007) Mhbounds-sensitivity analysis for average treatment effects. <http://ftp.iza.org/dp2542.pdf>. Accessed 23 Feb 2018
- Bonabana-Wabbi J (2002) Assessing factors affecting adoption of agricultural technologies: the case of Integrated Pest Management (IPM) in Kumi District, Eastern Uganda (Masters dissertation, Virginia Tech). <https://vtechworks.lib.vt.edu/handle/10919/36266>. Accessed 23 Feb 2018
- Brüssow K, Faße A, Grote U (2017) Adopting climate-smart strategies and their implications for food security. <http://www.tropentag.de/2015/abstracts/full/584.pdf>. Accessed 23 Feb 2018
- Dieterich C, Huang A, Thomas AH (2016) Women's opportunities and challenges in sub-Saharan African job markets. <https://www.imf.org/external/pubs/ft/wp/2016/wp16118.pdf>. Accessed 23 Feb 2018
- Food and Agriculture Organization (2013) Sourcebook on climate smart agriculture, forestry and fisheries. FAO, Rome. <http://www.fao.org/climatechange/374910c425f2caa2f5e6f3b9162d39c8507fa3.pdf>. Accessed 23 Feb 2018
- Jellis GJ (2009) Crop plant resistance to biotic and abiotic factors: current potential and future demands. In: Proceedings of the 3rd International Symposium on Plant Protection and Plant Health in Europe, Julius Kühn-Institut, Berlin-Dahlem, Germany, 14–16 May 2009, pp 15–21
- Joshua Udoh E, Titus Omonona B (2008) Improved rice variety adoption and its welfare impact on rural farming households in Akwa Ibom State of Nigeria. *J New Seeds* 9(2):156–173
- Khatri-Chhetri A, Aggarwal PK, Joshi PK et al (2017) Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agric Syst* 151:184–191
- Makate C, Wang R, Makate M et al (2016) Crop diversification and livelihoods of smallholder farmers in Zimbabwe: adaptive management for environmental change. *Springerplus* 5(1):1–18
- Manda J, Alene AD, Gardebroek C et al (2016) Adoption and impacts of sustainable agricultural practices on maize yields and incomes: evidence from rural Zambia. *J Agric Econ* 67(1):130–153
- Markandya A, Cabot C, Beucher O (2015) Economic assessment of the impacts of climate change in Uganda. https://cdkn.org/wp-content/uploads/2015/12/Uganda_CC-economics_Final-Report2.pdf. Accessed 23 Feb 2018
- Mswoya K, Madani K, Davtala R et al (2016) Climate change impacts on maize production in the warm heart of Africa. *Water Resour Manag* 30(14):5299–5312
- Mwongera C, Shikuku KM, Twyman J, Winowiecki L, Ampaire A, Koningstein M, Twomlow S (2014) Rapid rural appraisal report of Northern Uganda. International Center for Tropical Agriculture (CIAT), CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). <https://cgspace.cgiar.org/rest/bitstreams/32075/retrieve>. Accessed 23 Feb 2018
- Mwungu CM, Mwongera C, Shikuku KM et al (2017) Survey data of intra-household decision making and smallholder agricultural production in northern Uganda and southern Tanzania. *Data Brief* 14:302–306
- Nyasimi M, Kimeli P, Sayula G et al (2017) Adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, north-east Tanzania. *Climate* 5(3):63
- Odame H, Kimenyi L, Kabutha C et al (2013) Why the low adoption of agricultural technology in eastern and central Africa? In: Selected paper prepared for presentation at the Association for Strengthening Agricultural Research in Eastern and Central Africa conference, Entebbe, Uganda, 21 Oct 2011, pp 21–23
- Shiferaw B, Tesfaye K, Kassie M et al (2014) Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: technological, institutional and policy options. *Weather Clim Extremes* 3:67–79
- Shikuku K, Mwongera C, Winowiecki L (2015) Understanding farmers' indicators in climate-smart agriculture prioritization in Nwoya District, northern Uganda. *Centro Internacional de Agricultura Tropical, Cali (Publicación CIAT No. 412)*. <https://cgspace.cgiar.org/rest/bitstreams/65373/retrieve>. Accessed 23 Feb 2018

- Simtowe F, Muange E, Munyua B et al (2012) Technology awareness and adoption: the case of improved pigeon pea varieties in Kenya. In: Selected paper prepared for presentation at the International Association of Agricultural Economists Triennial Conference, Foz do Iguaçu, Brazil, 18–24 Aug, 2012 pp 18–24
- Tesfaye S, Bedada B, Mesay Y (2016) Impact of improved wheat technology adoption on productivity and income in Ethiopia. *Afr Crop Sci J* 24(s1):127–135

Open Access This chapter is licensed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

